

Denoising of MR Images using Non Linear Anisotropic Diffusion Filtering as a Preprocessing Step

Sankar Seramani, Zhou Jiayin, Chan Kap Luk, N.Malmurugan and A.Nagappan

Abstract: Magnetic resonance imaging (MRI) is a noninvasive method for producing tomographic images of the human body and it is most often used for the detection of tumors(lesions) and other abnormalities in soft tissues such as the brain. MR Images often requires application of noise filtering techniques before visual inspection or application of noise sensitive post processing methods, so a filtering which is desired to significantly decrease image noise and simultaneously to preserve some fine details in the image is required. Therefore good denoising technique should be developed on MRI for further processing the Lymph node for automatic segmentation.. In this paper Non Linear Anisotropic Diffusion Filtering denoising technique is discussed and its results were compared to the existing wavelet based denoising technique.

Index Terms: MRI, tumor, brain, segmentation, diffusion filtering, non linear

1.INTRODUCTION

Magnetic resonance imaging technique provides access to important anatomical and functional information through high speed acquisition. In MRI applications, there is an intrinsic trade off between signal to noise ratio (SNR), contrast to noise ratio (CNR) and resolution. Depending on specific diagnostic task, high spatial resolution and high contrast may be required, whereas for image processing applications, a high SNR is usually required, since most of the post processing segmentation algorithms are very sensitive to noise. Nonlinear anisotropic diffusion filters are iterative tunable filters introduced by Perona and Malik [1] for the removal of background noise in images. They have shown that diffusion filters can be used to enhance and detect object edges within images. It uses local gradients to control the anisotropy of the filter. Since these filters smooth or enhance MR images and detect edges they might also be used for RF correction and intracranial boundary detection in MR images [2]. Perona and Malik formulate the anisotropic diffusion filter as a diffusion process that encourages intra-region smoothing while inhibiting inter-region smoothing.

In medical imaging we often face a relatively low SNR with good contrast, or a low contrast with good SNR. Fortunately human visual system is effective in recognizing structures even in the presence of a considerable amount of noise. But if the SNR is too small or the contrast is too low it becomes very difficult to detect anatomical structures [3].

Low pass filtering reduces the amplitude of the noise fluctuations, but also degrades sharp details such as lines or edges. This type of filtering does not respect region boundaries or small structures, and the resulting images appear blurry and diffused. In case of linear diffusion filters the price of eliminating the noise is blurring of edges, which leads to the undesirable effects on the original image. This undesirable effects can be reduced or avoided by the design of non linear filters, the most common filtering being median filtering. In median filters the edges are retained, but the filtering results in the loss of resolution by suppressing fine details. Recently Wavelet based methods are becoming popular in preprocessing of Bio-images [5].

Spatial filtering techniques are applied under following assumptions they are (i) The image is supposed to consist of many regions in which signal is stationary and ergodic in mean and the variance (ii) The image noise is assumed to be zero mean and Gaussian distributed. The main problem is to find the stationary region. The problem of finding the proper stationary area for local signal estimation is partly solved by choosing filters that are able to distinguish homogeneous regions from those with edge regions. This anisotropic non linear filter assumes the image noise to be Gaussian distributed.

Recently developed anisotropic diffusion filtering [1], which overcomes the major drawbacks of conventional spatial filtering and significantly improves the image quality. Anisotropic diffusion filtering is a multistage smoothing and edge detection scheme, it can be formulated as a diffusion process, and encourages intra region smoothing in preference to smoothing across the boundaries. In this method the estimation about the local image structure is guided by knowledge about the statistics of the noise degradation and the edge strengths [3].

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This paper is organized as follows. Section II discuss the basic mathematical principles of non-linear anisotropic diffusion filters and 1-D anisotropic diffusion filtering. Section III briefs the extension of 1-D anisotropic diffusion filtering to 2-D anisotropic diffusion filtering. Section IV discusses the Proposed method of denoising of MR Images using Non linear anisotropic diffusion filtering and Section V gives the results and discussion. Finally Section VI gives the conclusion.

II. MATHEMATICAL PRINCIPLES OF NONLINEAR ANISOTROPIC DIFFUSION FILTER

Smoothing is formulated as a diffusive process, which is suppressed or stopped at boundaries by selecting locally adaptive diffusion strengths. In any dimension this process can be formulated as the equation given below, assuming no sinks or sources[3]

$$\frac{\partial}{\partial t} u(\bar{x}, t) = \text{div}(c(\bar{x}, t) \nabla u(\bar{x}, t)) \quad (1)$$

The diffusion strength is controlled by $c(\bar{x}, t)$. The vector \bar{x} represents the spatial coordinate(s). The variable t is an ordering parameter. The function $u(\bar{x}, t)$ is taken as image intensity $I(\bar{x}, t)$.

Two different diffusion function has been proposed, they are given below

$$c_1(\bar{x}, t) = \exp \left(- \left(\frac{|\nabla I(\bar{x}, t)|}{\kappa} \right)^2 \right) \quad (2)$$

$$c_2(\bar{x}, t) = \frac{1}{1 + \left(\frac{|\nabla I(\bar{x}, t)|}{\kappa} \right)^{1+\alpha}} \Big|_{\alpha > 0} \quad (3)$$

where κ is the diffusion constant, it is chosen to preserve the edge of the object boundary and to reduce noise contribution

The diffusion function $c(\bar{x}, t)$ depends on the magnitude of the gradient of the image intensity. Its a monotonically decreasing function, which mainly diffuses within regions and does not affect region boundaries at location of higher gradients [3].

$$c(\bar{x}, t) = f \left(\left| \nabla I(\bar{x}, t) \right| \right) \quad (4)$$

If the gradient is large, a discontinuity is assumed and the diffusion is halted. The parameter κ is chosen according to the noise level and the edge strength. To understand the relation between the parameter κ and the discontinuity

value ∇I , it is proposed to define as the product, $c * \nabla I$ called flow. The flow functions related to c_1 and c_2 are plotted in the Figure 2.1 below for various values of κ and ∇I .

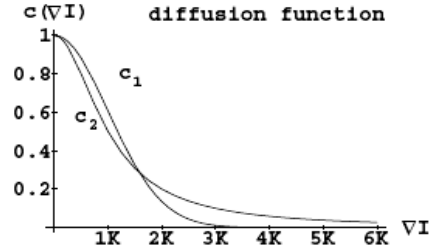


Figure 2.1: Flow functions for c_1 and c_2 with respect to κ and ∇I

The maximum flow is generated at locations with gradient ∇I equal to κ . When decreasing below κ , the flow reduces to zero, because in homogeneous regions only minimal or no flow takes place. Above κ the flow function again decreases to zero, halting diffusion at locations of higher gradients. A proper choice of the diffusion function not only preserves, but also enhances the edges. The anisotropic diffusion process can be described as a piecewise smoothing of the original signal. The assumption of piecewise constant or slowly varying intensity is a good estimate to model MR image data, which comprise smooth regions separated by discontinuities, representing various tissue categories distinguished by different proton densities and relaxation properties[4].

1-D Anisotropic Diffusion Filtering:

The intensity change in one iteration step is defined as the sum of flow contributions between the neighboring pixel intensities. The structure is simulated as a network, wherein the centre point of pixel represent nodes and are linked together by arcs, whose flow characteristics are determined by the conductivity function Φ [4]. The network structure for the 1-D filter is given in Figure 2.2 below.

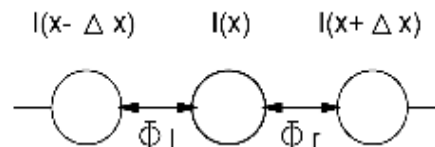


Figure 2.2: The network structure for 1-D diffusion filters [2]

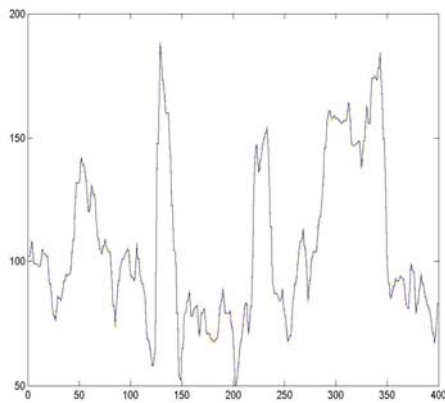
The 1-D discrete implementation of the diffusion process is defined by the following set of equations as

$$\begin{aligned}
 \frac{\partial}{\partial t} I(x,t) &= \text{div}[c(x,t) * \text{grad} I(x,t)] = \nabla^T [c(x,t) * \nabla I(x,t)] \\
 &= \frac{\partial}{\partial x} \left[c(x,t) * \frac{\partial}{\partial x} I(x,t) \right] \\
 &\approx \frac{\partial}{\partial x} \left[c(x,t) * \frac{1}{\Delta x} \left(I(x + \frac{\Delta x}{2}, t) - I(x - \frac{\Delta x}{2}, t) \right) \right] \\
 &\approx \frac{1}{\Delta x^2} \left[c(x + \frac{\Delta x}{2}, t) * (I(x + \Delta x) - I(x)) - c(x - \frac{\Delta x}{2}, t) * (I(x) - I(x - \Delta x)) \right] \\
 &= \Phi_{\text{right}} - \Phi_{\text{left}} \quad |\Delta x = 1
 \end{aligned} \quad (5)$$

As the first step the signal flow is calculated between neighboring nodes as given above. Then the node intensities are updated by the local sum of the flow contributions are given as

$$I(t + \Delta t) \approx I(t) + \Delta t * \frac{\partial}{\partial t} I = I(t) + \Delta t * (\Phi_r - \Phi_l) \quad (6)$$

The effect of anisotropic filtering in 1-dimension along the row is shown in Figure 2.3 and Figure 2.4 which shows the smoothing effect (a) before and (b) after anisotropic diffusion filtering, considerable noise smoothing effects can be seen without smoothing out the edges



(a)

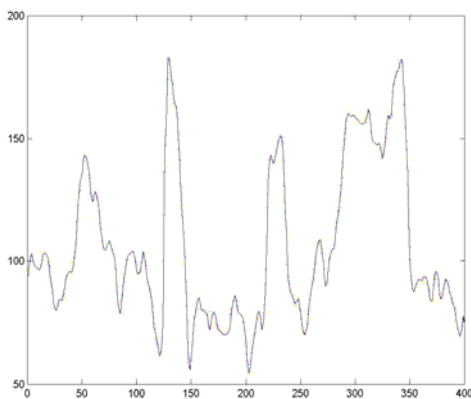
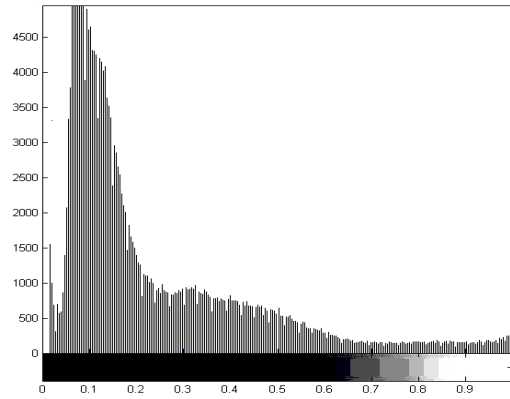
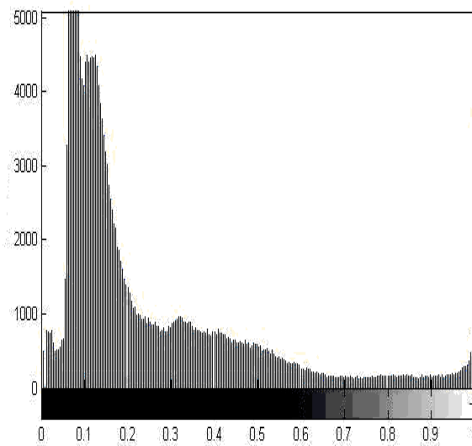


Figure 2.3: One dimensional signal extracted from the T2 Image (a) before anisotropic filtering (b) after anisotropic filtering to show the effect of edge preserving filtering



(a)



(b)

Figure 2.4: Histogram of (a) T2 image before anisotropic filtering (b) after anisotropic filtering

III. 2D NONLINEAR ANISOTROPIC DIFFUSION FILTER

It's a simple extension of the 1-D discrete implementation. The 2-D discrete implementation of the diffusion process is defined by the following set of equations as

$$\begin{aligned}
 \frac{\partial}{\partial t} I(\bar{x}, t) &= \text{div}[c(\bar{x}, t) * \text{grad} I(\bar{x}, t)] = \nabla^T [c(\bar{x}, t) * \nabla I(\bar{x}, t)] \\
 &= \frac{\partial}{\partial x} \left[c(\bar{x}, t) * \frac{\partial}{\partial x} I(\bar{x}, t) \right] + \frac{\partial}{\partial y} \left[c(\bar{x}, t) * \frac{\partial}{\partial y} I(\bar{x}, t) \right] \\
 &= \frac{1}{\Delta x^2} \left[c(x + \frac{\Delta x}{2}, y, t) * (I(x + \Delta x, y) - I(x, y)) - c(x - \frac{\Delta x}{2}, y, t) * (I(x, y) - I(x - \Delta x, y)) \right] + \\
 &\quad \frac{1}{\Delta y^2} \left[c(x, y + \frac{\Delta y}{2}, t) * (I(x, y + \Delta y) - I(x, y)) - c(x, y - \frac{\Delta y}{2}, t) * (I(x, y) - I(x, y - \Delta y)) \right] \quad (7)
 \end{aligned}$$

The signal flow between neighboring nodes can be computed as

$$\frac{\partial}{\partial t} I(x, t) = \Phi_{east} - \Phi_{west} + \Phi_{north} - \Phi_{south} \quad (8)$$

The node intensities are updated by the local sum of the flow contributions are given as

$$I(t+\Delta t) \approx I(t) + \Delta t \frac{\partial}{\partial t} I = I(t) + \Delta t (\Phi_e - \Phi_w + \Phi_n - \Phi_s) \quad (9)$$

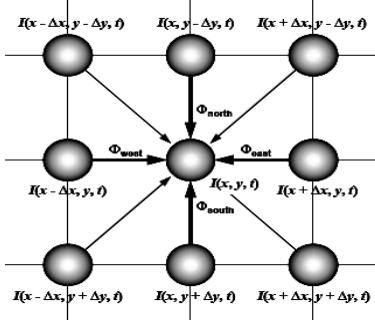


Figure 3.1: The network structure for 2-D diffusion filter

To obtain better isotropy, flow is also calculated between diagonally neighbouring pixels, resulting in an eight way connected network. The longer distance between diagonal neighbors is taken into account by setting Δd to $\sqrt{2}$ [3].

IV. PROPOSED METHOD OF DENOISING OF MR IMAGES USING NONLINEAR ANISOTROPIC DIFFUSION FILTERING

The MRI image to be enhanced is preprocessed before applying linear anisotropic diffusion filtering for selecting proper region of interest. After applying filtering technique, it has to be checked for its quality with expert opinion. This depicted in Fig 4.1.

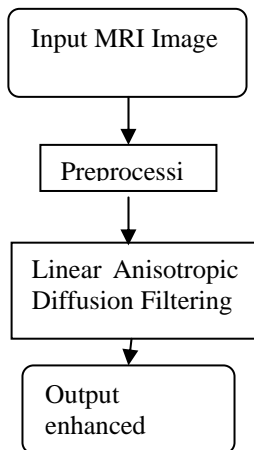


Fig. 4.1. The Flow chart for the proposed method of enhancement

V. RESULTS AND DISCUSSION

Retrospective denoising with a nonlinear technique such as anisotropic diffusion filtering has been demonstrated

to be an attractive option for improving the SNR of the Magnetic Resonance Images. Thus Anisotropic diffusion filtering has proved to be particularly effective in prefiltering of MR images before the automatic image segmentation procedure

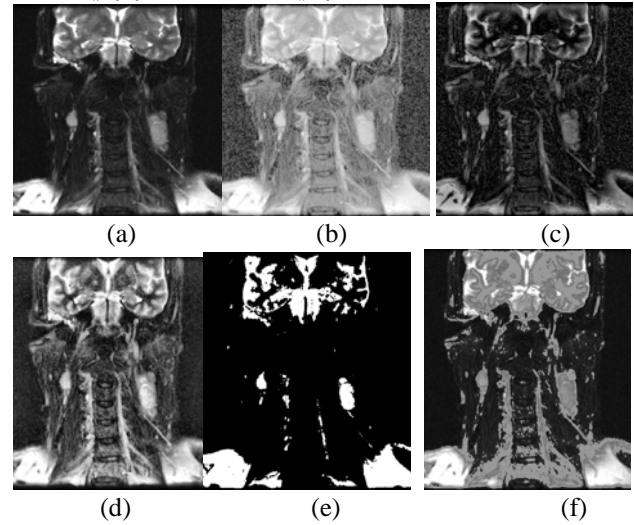


Figure 5.1. Images after enhancement (a) Original image (b) after histogram equalization (c) after applying Modified Retinex algorithm (d) after Contrast limited Histogram equalization (e) after applying adaptive thresholding (f) after applying unsharp masking

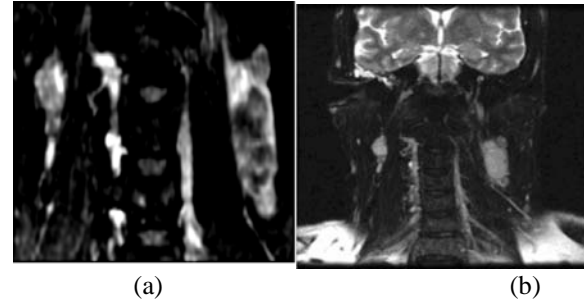


Figure 5.2 (a) Images after enhancing with symlet wavelet by taking ROI (b) Image after 2-D anisotropic diffusion filtering

The visual observation is better in 2-D anisotropic diffusion filtering than that of wavelet based enhanced image and that the existing algorithms like adaptive unsharp masking, contrast limited adaptive histogram equalization and other algorithms. This is evident in Figure 5.1 and 5.2

VI. CONCLUSION

The power of the anisotropic smoothing scheme proposed herein lies in the fact that it deals with local estimates of underlying image structures, which are highly flexible. Discontinuities are preserved and their position is not affected. Anisotropic diffusion filtering is an accepted filtering technique that is well suited for practical use

because of its computational speed and algorithmic complexity. Hence the proposed filter can yield highly efficient noise reduction and the ability to preserve and even enhance important image structures for improved visual detection of abnormal tissues in medical image diagnostics.

VII. REFERENCES

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